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Learning Schemes using Neural Networks for Cognitive Radio: A survey

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Abstract: The future of wireless system is facing the problem of spectrum scarcity. Number of users is increasing rapidly but available spectrum is limited. The Cognitive Radio (CR) technology enables the unlicensed users to share the spectrum with the licensed users on a dynamic basis without creating any interference to primary user. Three fundamental tasks are performed by cognitive radio i. e. sensing, learning and reasoning in cognitive radio network. The importance of learning techniques to be implemented in cognitive radio has been discussed. Previous work based on learning schemes using artificial neural networks has been described in this paper, which motivates and guides to do research. Here we confer the use of neural networks in research for various types of learning schemes in cognitive radio technology.

Keywords: Cognitive Radio, Wireless Communication, Neural Networks, Learning Schemes.

I. INTRODUCTION

In wireless communication network proper utilization of radio frequency spectrum is the prime consideration. The frequency spectrum is not used efficiently due to nonflexible allocation of its license for use. These licenses are controlled by government agencies and are assigned to service providers for long duration and huge geographical area. DARPA has done measurements for signal strength distribution for frequency spectrum used for wireless communication and observed that some bands are so overcrowded that its access is a major problem and very large portion of this spectrum is underutilized. Then research went on to implement such a radio that can detect and use the vacant frequency spectrum for data transmission [1]. In addition to this if it can also remember the geographical location and time the list of vacant channels. These few ideas motivated the research and development in the field of cognitive radio [2]. So cognitive radio is a software defined radio which can exploit the underutilized spectrum called spectrum holes, for which the following definition has been offered: "A spectrum hole is a band of frequencies assigned to a primary user, but, at a particular time and specific geographic location, the band is not being utilized by that user".

II. NEED FOR LEARNING SCHEME

Cognitive capabilities need to be embedded in radio to improve the spectrum efficiency. Cognitive radio changes its behavior according to environmental changes or changes in principles, goals and capabilities. In future cognitive radios will be able to change its configuration on the fly with the help of stored database and learning capabilities for managing and representing information and practical experience. For simplicity the working of a cognitive radio can be represented as a cognitive cycle, having three phases: sensing the environment, estimation and predictive modeling, decision for selection of radio configuration as shown in Fig. 1. Radio configuration refers to its carrier frequency, power for transmission and type of modulation etc.

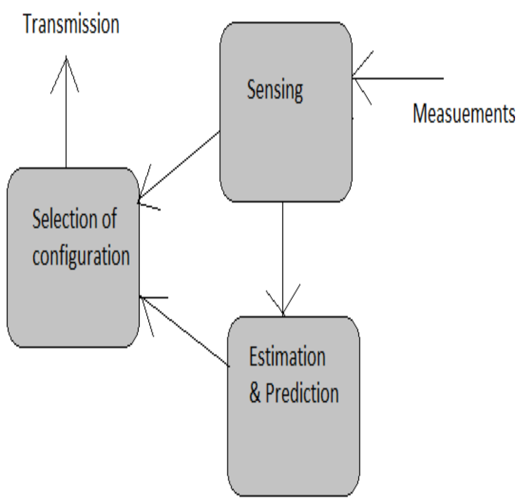

Fig.1: Representation of cognitive radio cycle

Cognitive radio can be considered as an enhancement of software defined radio with additional capabilities of intelligence called cognitive engine (CE) as shown in Fig 2. This cognitive engine takes decisions based on observations and stored database about the selection of Radio access technology and enforces them to software defined radio (SDR) so that radio can operate in desired state for better performance. Cognitive engine is able to learn lessons and update the database continuously. This process helps it to take decisions and future actions.

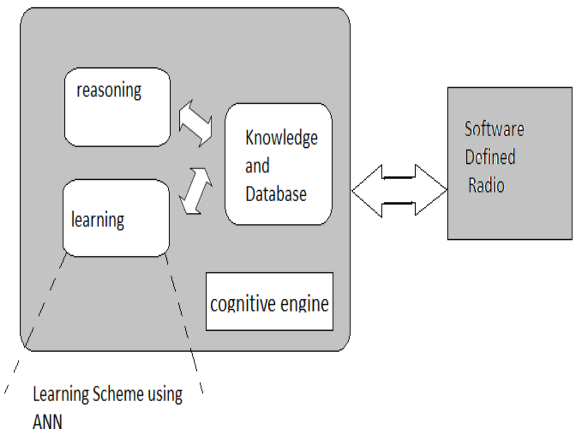

Fig. 2: Cognitive radio engine

Reasoning module of CE can determine the executable actions in a particular state of environment. This process of reasoning takes lot of time and its computational complexity is very high in case of large number of state-action combinations. Reasoning can be improved by learning through elevating the database of knowledge which is to be used in process of reasoning. Prevailing reasoning can improve the effectiveness of learning by giving relevant examples for learning in return. Both capabilities along with awareness improve the performance of cognitive radio network.
This leads to importance of learning module in Cognitive Engine. For the channel estimation and predictive modeling phase of cognitive cycle, the implementation of learning module is very important for taking decision about next stable and reliable radio configuration, taking into consideration not only the present observations but previous measurements also.

III. LEARNING SCHEMES IN CE

The technologies and phenomena using various artificial neural networks which have been used to embed intelligence in cognitive radios available in literature are discussed in this section.

Authors in paper [3] have proposed two models to forecast the occurrence of an incident. The relationship between real-time traffic data and incident duration has been developed with 40% error. Real-time traffic data taken as input variable are collected from loop vehicle detectors. The incident duration is taken as an output variable. It helps to forecast the variation of traffic situation and incident occurrence. In papers [4]–[5] authors have described the importance of integration of a learning engine for predictive modeling phase and channel estimation to improve the reliability and stability of cognitive radio network. To achieve this many artificial intelligent techniques can be used like hidden Markov models, reinforcement learning, genetic algorithms and artificial neural networks as mentioned in research. Two learning schemes based on artificial neural networks have been proposed in these papers, basic and extended. The first one is designed to improve the capability of learning of the cognitive radio by providing the prediction of data rate for a particular radio configuration in that environment and also to perform its benchmarking and discuss its usefulness for future cognitive users. Minimum root mean square error of the designed network is 0.0549. The second one stresses that the basic learning scheme should be extensible and flexible to accumulate the further information data in this process. Performance parameter, minimum root mean square error of the proposed network is found to be 0.0468. The limitations of these papers are that some crucial, important information has not been used to feed the neural network and new types of NNs have not been explored.

Adaptive radio resource management system has been proposed to increase the capacity of a GSM network in [6]. Neural networks have been used to predict the future requirement of resources for each cell in the network.
A Multilayer Perception (MLP) artificial neural network based learning scheme to learn the behavior of spectrum is proposed in [7]. This network is used to predict the state of various channels in future using supervised learning. It helps the cognitive user to handover transmission to new channel without interruption. Performance has been evaluated in terms of mean Root Mean Square Error (RMSE) as 0.08. The feed-forward random neural network model and learning algorithms are discussed in [8]. The activation of normal neuron is either a continuous variable or a binary variable but for neuron in random neural network represented by its potential. It is said to be in firing state if its potential is positive and is more granular as compared to other neuron.

In paper [9] authors have proposed Multilayered Feed-forward Neural Networks (MFNN) for depiction of performance evaluation functions in cognitive radio.
The shortage of bandwidth is main reason for blocked and dropped calls. As analogue TV broadcast bands of 700 MHz are getting vacant due to its digitization, mobile operators are demanding for these bands to deploy 4G and 5G services. In some countries migration of analogue to digital TV will take some time. An intelligent wireless system based on artificial neural networks to use the vacant licensed channels has been proposed in [10]. In this research work, performance of the proposed network is evaluated in terms of MSE which comes out to be 0.06666. A learning algorithm using feature based neural network has been proposed in [11]. This network is able to predict the distribution of received radio signal as a function of its location. Virtual environment model have been produced. Model parameters are scattering bodies

and reflective walls. The wireless signal strength was measured at stochastic positions and used for training. Then the proposed trained network used to predict the strength of radio signal. MSE has not been quantified but it has been stated that MSE is quite high in this network.
A cellular neural network and utility (CNNU)-based radio resource scheduler has been proposed in [12]. It adopts cellular neural network to solve the difficult optimization intricacy of the forecast algorithm for communication systems.

A neural network based model has been designed to predict the presence of spectrum by authors in [13]. It is a multilayer perceptron without requirement of prior knowledge of the signal and behavior of primary user. Results in this research show that accuracy after training can be achieved is 93.6% and after retraining it can improve to 96%.

An Adaptive Resonance Theory-2 (ART-2) neural network channel sensing algorithm for wireless mesh network has been proposed in [14]. Simulation results show its accuracy 98.5% which is higher than the accuracy of Bayesian network which is 97%.

In paper [15] authors have proposed a design of cognitive engine, and used a training algorithm based on artificial neural network to implement a learner in it. A multilayer perceptron (MLP) neural network model have been considered to ensure the convergence of the network, over fitting and problems on stop condition. It has been observed that neural network with 2 hidden layers converged fastest as compared to network with more number of hidden layers and RMSE is around 4.3%.

A scheme based on Artificial Neural Networks to allocate the spectrum in cognitive radio system has been proposed in [16]. Authors have analyzed single user with different time and multi-user with different weights. It has been observed that the proposed scheme can replace the complicated frequency allocation scheme used earlier.

Researchers in [17] have combined Genetic algorithm (GA) and Radial Basis Function Neural Network to implement learning capability in cognitive engine. The first one is good to optimize multiple objectives and the second one has ability of strong learning. Mean square value (MSE) and regression rate (RR) are taken as performance parameters for BP, RBF and GA_RBF learning mode. The average MSE and RR for three structures are 0.2641, 48.60%, 0.0254, 97.60%, 0.0215, 99.80%.

Artificial neural network based spectrum sensing technique has been proposed in paper [18]. Performance analysis proves that this scheme is suitable to detect the signals under low SNR and is reliable. MSE comes out to be 2.70142×10^{-6}.

The network proposed by authors in [19] has been trained using statistical primary user data for mobile communication and can be embedded in control unit of secondary users. This proposed learning scheme will not only save time and energy for spectrum sensing but also improves spectrum utilization. The performance parameter mean square error of the proposed network is $2.1773\text{x}10^{-11}$.

We have discussed the work of many researchers till now. Results of some of them are presented here in Table 1.

TABLE 1: Results of previous work in tabular form:

S. No.	Researcher	Technique used	Error/MSE/RMSE
1	Chien-Hung Wei et al., 2007 [3]	Multi-layered Perceptron	MSE= $3.4\text{ x}10^{-4}$
2	Xiang-lin Zhu et al., 2008 [14]	ART2	MSE =$1.5\text{x}10^{-2}$
3	K. Tsagkaris et al., 2008 [4]	Focused Time Delay	MSE = 0.0549 =$5.4\text{ x }10^{-2}$
4	Katidiotis et al., 2010 [5]	Focused Time Delay	MSE = 0.0194 = $1.9\text{ x }10^{-2}$
5	Liang Yin et al., 2011 [7]	Multi-layered Perceptron	RMSE =.08 MSE= $6.4\text{x}10^{-3}$
6	Ojenge Winston et al., 2013 [10]	Multi-layered Perceptron	MSE = 0.066666 = $6.6\text{x }10^{-2}$
7	Vamsi Krishna Tumuluru et al., 2010 [13]	Multi-layered Perceptron	Accuracy = 96% MSE = $4\text{ x }10^{-2}$
8	XuDongi et al., 2010 [15]	Multi-layered Perceptron	RMSE = $4.3\text{x }10^{-2}$
9	Yanchao Yang et al., 2012 [17]	GA Radial Basis GA+Radial Basis	MSE = $2.641\text{x }10^{-1}$, MSE = $2.54\text{x }10^{-2}$, MSE = $2.15\text{x }10^{-2}$.
10	Yu-Jie Tang et al., 2010 [18]	Multi-layered Perceptron	MSE = 2.70142×10^{-6}
11	Mahajan R et al., 2016 [19]	Multilayered Perceptron	MSE = $2.1773\text{x}10^{-11}$

IV. CONCLUSION

It can be easily observed from this paper that artificial neural networks have been successfully used to embed cognition in cognitive engine to derive software defined radio. Root Mean Square Error (RMSE) or Mean Square Error (MSE) and prediction accuracy have been used as performance index to evaluate them. In this survey paper we have discussed the use of different learning models of Artificial Neural Network proposed in literature.

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